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Radical or incremental: Where does R&D policy hit?*

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Abstract

This study investigates the impact and effectiveness of a public R&D support policy. In a policy design that aims at incentivizing radical as well as incremental innovations, we test where the policy impact is highest. While the privately motivated R&D expenditures are significant for both types of innovation, the policy-induced part is significant only for radical innovation. Furthermore, given that the funding agency encourages collaboration, and particularly industry-science collaboration, we further test whether effects are enhanced in collaborating firms. We do not find any evidence pointing to increased effects for the latter.

Keywords: R&D subsidies; collaborative innovation; innovation performance; radical innovation; incremental innovation; policy evaluation; treatment effects.

JEL-Classification: C14, C30, H23, O31, O38

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1. INTRODUCTION

Innovation is largely acknowledged to be a main factor of a country's sustainable and competitive development (Aghion & Howitt, 1992; Griliches, 1990; Romer, 1990). It is also recognized that due to market imperfections, firms are unlikely to reap all the benefits from their research, leading to underinvestment in R&D in the economy. Therefore, governmental support is a widely accepted means to foster socially valuable innovation.

The concept of market imperfection goes back to Nelson (1959) and Arrow (1962), who state that firms do not invest the socially desired level in R&D efforts due to market imperfections including limited approbiability, lower private than social returns, financial market constraints, high risks about technological standards, high costs and high uncertainty of R&D projects and further forms of negative externalities (Martin & Scott, 2000). The implications of this under-investment in R&D have encouraged policy makers to establish public support mechanisms. In the current paper, we are interested in one particular type of support, namely direct funding for R&D projects. More precisely, we aim at contributing to an on-going debate about the returns of public R&D funding (Jones & Williams, 1998; Salter & Martin, 2001), and in particular about whether public money is used in the most effective way (David & Hall, 2000; David, Hall, & Toole, 2000; Klette, Møen, & Griliches, 2000). In order to do so, we investigate the impact of the Swiss public support policy on outcome characteristics that have so far largely been ignored in this stream of literature. Specifically, we analyse where the policy effect is highest: incremental or radical innovation.

Based on the market failure theory stipulating that under-investment in R&D may be particularly pronounced for more radical innovations because of higher uncertainty linked to such projects, one may expect to see an effect of public support on radical rather than on incremental innovation. Indeed, as shown by Karlsson, Friis, and Paulsson (2004) for instance, there is a higher probability of no returns on investment for more radical innovation when compared to incremental innovation. Likewise, given the riskier nature of such projects, firms may have more difficulties to find external funding (see e.g. Kamien & Schwartz, 1978). As a consequence, given that funding agencies want to stimulate projects which are socially desirable but would not be undertaken without public support, one would assume that the impact is particularly pronounced for the latter. In the case of the Swiss innovation policy, the goal is however not merely destined at promoting frontier breaking innovation but also to maintain or enhance the competitiveness of the recipient firms, which can be achieved through incremental and radical innovations alike. It is therefore of high interest to know if the created impact is the same for both types of projects or if one type yields more returns than the other.

For the policy maker, such information is crucial in order to optimize the policy structure. Indeed, it is essential to know if the ex-ante project evaluation is appropriate to prevent firms from crowding-out of private R&D expenditures due to public R&D funding. Consequently, in a first step, we investigate the effectiveness of the policy scheme and test if the subsidy leads to higher R&D expenditures. In a second step, we analyse how this policy induced R&D expenditures translate into innovation output, differentiating between radical and incremental innovation. Indeed, even in case of positive input additionality (meaning higher R&D expenditures due to the subsidy), it remains unclear if the policy induced R&D is as productive as the privately induced R&D. Indeed, based on portfolio maximization theory, firms spent their private money first on projects with the highest expected returns. In case of equal (or even higher) productivity, it remains so far indeterminate whether the impact is highest for more radical or more incremental innovation projects. Therefore, a first and main contribution of this paper lies in disentangling the effects of privately invested and publicly induced R&D on innovation outcome, according to the degree of novelty of the products.

Our second contribution pertains to taking into account the firms' collaboration status. It has been proven that R&D collaboration is likely to impact innovation performance due to spillover effects, risk and cost sharing. Collaboration is therefore encouraged by the funding agency. Taking collaboration as well as the type of collaboration into account is therefore crucial as it can advise policy makers on the efficiency of this policy criterion. Within the various collaboration types, the Swiss funding agency particularly encourages collaboration with science. Shedding light on whether collaboration has an important impact on innovation outcome as well as what type of collaboration (i.e. is it mainly science, as encouraged by the agency or do other partners also play a role?) seems therefore particularly relevant in this context. So far, the literature does not advice on this issue, as the impact of the type of partner in a subsidy scheme has not been analysed in previous papers. Indeed, most papers in the evaluation literature merely account for R&D collaboration (if at all), but do not pay attention to partner diversity.

Thirdly, the present study is undertaken on a representative sample of Swiss firms, which despite being considered an innovation leader among OECD countries, has not received as much attention as many other countries on this subject.

Finally, in contrast to most policy evaluation studies, our analysis also allows drawing conclusions from a managerial perspective. Knowing where the impact of an R&D subsidy is highest in order for them to best adapt grant application efforts to innovation strategies plays indeed an important role. Likewise, knowing whether input and/or output additionality is enhanced through collaboration (as well as through the type of partner) seems essential information for a manager to optimize its R&D project portfolio.

We base our analysis on a representative firm-level data-set covering the period between 1999 to 2011 of the Swiss innovation survey. We find that, on average, the receipt of an R&D

subsidy translates into higher R&D investment. In terms of innovation performance, we find that the impact of public support is only significant for radical innovation, while no impact of policy-induced R&D is found for incremental innovation. Privately financed R&D on the other hand is significant for both types of innovation. In terms of collaboration, we do not find evidence that the impact of the policy is improved through collaboration. We can thus conclude that while the Swiss public R&D policy is efficient in terms of stimulating R&D investment and innovation performance of more radical nature, the current tendency of encouraging R&D collaboration does not seem to enhance such effects.

2. INSTITUTIONAL CONTEXT OF THE SWISS INNOVATION POLICY

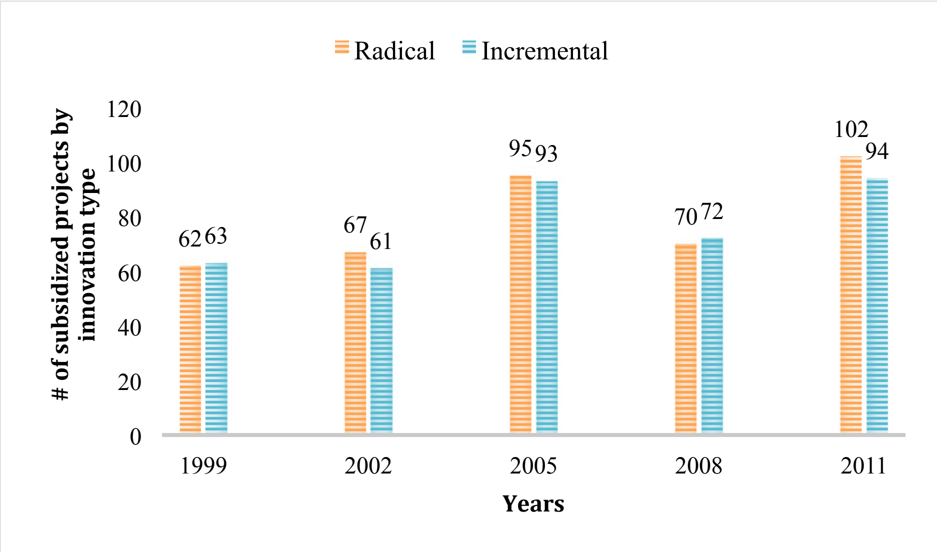
Many countries have launched innovation policy programs to promote national innovativeness and competitiveness. An outstanding performance in R&D and innovation activities is considered an important factor not only for economic growth but also for a sustainable economic perspective in terms of employment, ecology and education for a modern knowledge society. In Switzerland, public funding of R&D has increased by 5.3% between 2000 and 2010. In 2010, the financial budget for appropriations or outlays dedicated to R&D covers an amount of 4.6 billion CHF, which corresponds to 0.81% of the country's GDP. In an international comparison (measures from 2008), Switzerland holds the eleventh rank of 31 OECD countries with public R&D funding corresponding to 0.73% of the country's GDP. The United States (1.02%) and Finland (0.98%) are on the top positions of the public funding per GDP ratio (FSO, 2012).

In Switzerland there are two major R&D funding agencies providing public grants for R&D programs and projects—the Swiss National Science Foundation (SNSF) and the Commission for Technology and Innovation (CTI)—with a total budget of 1.0 billion CHF in 2010. While the SNSF is mainly in charge of providing public grants to R&D projects or programs conducted by public research institutes or by individual researchers, the CTI is the responsible funding agency for R&D projects in the private sector, with a total budget of 118 Mio CHF in 2010. As a consequence, the subsidies under review in this study mainly stem from the CTI.

The subsidy scheme is not based on calls for proposals, but firms can apply with R&D projects all year long. Likewise, there are no restrictions in terms of technology fields supported by the agencies. Nonetheless, the CTI has the general goal to stimulate innovation in SMEs and encourages joint R&D activities between private companies and public research institutes. The focus of the policy is two-fold: on the one hand, the agency provides support for applied and market-oriented R&D projects which lead to the generation of improved technologies and products to strengthen the country's innovation position (CTI, 2011). On the other hand, the CTI also supports high risk but promising, cutting-edge technologies. As can be seen in Figure 1 on the subsidy distribution by innovation type, there is hardly any difference between the number of subsidies going to firms with radical or incremental innovation output.[1]

[1] The distribution of subsidies across firm size classes and sectors can be found in Appendix 1, Tables A.1 and A.2.

Figure 1: Subsidy distribution by innovation type.



Source: Own calculations. Data derived from the Innovation survey conducted by the Swiss Economic Institute (KOF).

Applicant firms have to provide a detailed description on the project's impact and a clear business and financial plan. The ex-ante evaluation is done by external and internal referees, which evaluate the expected effectiveness of the R&D projects. In 2010, 780 projects were evaluated, and 343 (44%) projects have been retained for public support (CTI, 2013).

In case of a positive evaluation, the firm receives a subsidy in form of a matched grant, where the public funding typically covers up to approximately 50% of the expected costs (CTI, 2011, 2013). That is, the recipient firm always faces a co-financing clause by which is it held to finance half of the project costs from private resources. In 2010, 667 firms are involved in co-funded R&D projects, among which almost three quarters (74%) were SMEs (CTI, 2013). The average project duration is of 20 months and the average project size amounts to 682.2 thousand Swiss francs.[2] As can be seen by Table 1, the number of subsidized firms has remained very stable over the period under review.

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[2] Data about project duration is provided by ARAMIS, a database of the Swiss federal administration.

Table 1: Subsidy distribution over survey period 1999-2011.

Year	Number of firms	Percentages of non-subsidized firms	Percentages of subsidized firms
1997-99	1,140	90.70	9.30
2000-02	1,370	93.80	6.20
2003-05	1,310	90.61	9.39
2006-08	1,124	91.46	8.54
2009-11	1,140	88.07	11.93
Total	**6,084 (100%)**	**91.03 (on average)**	**8.97 (on average)**

3 OUR RESEARCH QUESTION IN LIGHT OF RECENT LITERATURE

3.1 The Impact of R&D support

Empirical evidence on R&D subsidies is common in the literature to date. In terms of input additionality, it has been shown that the null hypothesis of full crowding out can be rejected in the vast majority of cases. In other words, most studies find that firms receiving public support invest more in R&D than if they would not have been supported. The subsidy hence reaches its goal of stimulating R&D investment. Indeed, Hall and Maffioli (2008) have found that in empirical literature since 2000, total crowding out effects were only found for the US Small Business Innovation Research (SBIR) program, analysed by Wallsten (2000).[3]

In terms of output additionality, evidence confirms that subsidies have a positive impact on innovation performance, as measured for instance by patent outcome (see e.g. Czarnitzki and Hussinger (2004) or Czarnitzki and Licht (2006)) or novelty sales (see for instance Czarnitzki and Lopes-Bento (2014) for a sample of German firms or (Hottenrott and Lopes-Bento (2014a) for a sample of Belgian firms). In a recent study on Swiss firms, Arvanitis, Donze,

[3] See Czarnitzki and Lopes-Bento (2013) for an overview on relevant recent empirical studies; and Cerulli (2010) for a critical overview on the different applied methods.

and Sydow (2010) found evidence for improved innovation performance of supported firms with respect to six different measures of innovation performance.[4]

Papers distinguishing the productivity effects of privately respectively publicly funded R&D remain limited to date. Even though Madsen, Clausen, and Ljunggren (2008) suggest that input and output additionality are interrelated, to the best of our knowledge only Czarnitzki and Hussinger (2004), Czarnitzki and Licht (2006) and Hottenrott and Lopes-Bento (2014a) consider this disentanglement and find a positive impact of publicly induced R&D investment on patenting activities in German firms and novelty sales in Belgium firms respectively.

The latter do not differentiate between the degree of novelty in innovation sales though. Compared to the above studies, the current analysis further considers the disentangled investment in light of the degree of novelty of the innovation outcome. Indeed, one of the primary dimensions used to distinguish between degrees of innovation is the perpetuity between radical and incremental innovation (Garcia & Calantone, 2002; Tushman & Anderson, 1986). The former is typically defined as being new and different from prior solutions and the latter is characterized as making minor changes from (or adjustment to) existing practices, products, and services (Ritala & Hurmelinna-Laukkanen, 2013; Schilling, 2013)). As stipulated by Garcia and Calantone (2002), the difference between incremental and radical innovation is crucial. Radicalness is typically conceived as a combination of

[4] Their respective outcome variables include: Importance of introduced innovations from a technical point of view, Importance of introduced innovations from an economic point of view, Percentage reduction of average variable production costs due to process innovation, Sales of significantly improved or modified (already existing) products as a percentage of total sales, Sales of products new to the firm or to the market as a percentage of total sales, Sales of products new to the market worldwide as a percentage of total sales. While one of the main contributions of this paper was to compare the ATE of these outcome variables using 4 different matching estimators, it did not analyze how policy-induced investment translates into certain types of innovation performance when compared to privately-financed R&D investment at the firm level. As a consequence, it also did not take other firm or policy characteristics into account when estimating how the subsidy translates into output. The present study remedies to these shortcomings by estimating the treatment effect at the firm level, distinguishing between privately- and policy-induced investment in terms of innovation performance and by controlling for other relevant characteristics in this second step of the estimation, thereby providing novel and more in-depth policy implications.

newness and the degree of differentness (Ritala & Sainio, 2014). Therefore, radical innovation is not only capable of significantly impacting firm performance, but it also has the potential to change the structure of the market, to create new markets or to render existing products obsolete. Furthermore, radical innovations have the potential to push the technological frontier of a firm or even sector and may allow a firm to enter new markets. It is however also often involved with higher costs and higher risks, since it is typically embodied in new, and thereby less familiar, knowledge (Schilling, 2013). It may thus well be that projects of radical nature are less likely to be undertaken by firms left to themselves as firms have to be willing to bear the inherent risk of this endeavour. Furthermore, they also have to be able to provide the necessary funding for such projects, as due to the more risky nature, investors and external financiers are generally more reluctant to finance such projects (Czarnitzki, Hottenrott, & Thorwarth, 2011). Since the assumption is that firms are often risk-averse and financially constrained, this could lead to a sub-optimal allocation of radical vs. incremental innovation (Arrow & Lind, 1970).

Incremental innovations on the other hand can be considered the "lifeblood of an organization" (p. 123) because they act "first as a competitive weapon in a technologically mature market; and second, because streamlined procedures based on existing technology can help alert a business in good times to threats and opportunities associated with the shift to a new technological plateau" (Johne & Snelson, 1988, p. 115). Hence, incremental innovations are crucial to ensure small improvements to existing products, helping to maintain or improve their competitive position over time. They also play an undeniable role in adapting products or product lines to new or enhanced features increasingly desired by customers.

As a consequence, both types of innovation are important determinants for the success of a firm, both being of different nature and impacting the firm in different ways. Distinguishing these two types of innovation therefore constitutes an important characteristic in a policy evaluation context, as it allows to better orient the policy to the target or the priority of the economic context under review (Nemet, 2009).

However, it is difficult to predict ex-ante where the policy effect will be highest and whether the selection process of the funding agency is efficient in light of the type of innovation in which the additional investment will be destined to. This is precisely one of the gaps that this study aims to fil.

3.2 The impact of R&D collaboration

It has long been acknowledged that R&D collaboration plays an important role, for the type as well as the success of innovation projects. Allowing to limit outgoing spillovers by internalizing them to the research consortium and providing access to complementary know-how and resources of partnering firms, it has been shown that R&D collaboration can enhance private R&D activities substantially (see for instance D'Aspremont & Jacquemin, 1988; DeBondt, 1997; Kaiser, 2002; Kamien, Muller, & Zang, 1992; Katz, 1986).

Subsidized collaborative R&D has received less attention though in the empirical literature so far. Exceptions are Sakakibara (2001) and Branstetter and Sakakibara (2002) who analyzed Japanese government-sponsored R&D consortia. Both studies found evidence that participating firms have higher R&D expenditures as well as more patents. Further, Czarnitzki, Ebersberger, and Fier (2007) apply a matching estimator in a multiple treatment setting, analyze the effects of R&D collaboration and public R&D funding on R&D per sales and patent outcomes for Germany and Finland and find that collaboration has positive effects. Finally, Hottenrott and Lopes-Bento (2014a) find that in a sample of Belgian firms, international collaborating firms have a higher subsidy treatment effect than nationally or non-collaborating firms.

The aspect of various partner types (i.e. horizontal, vertical or collaboration with science) within a subsidy scheme has so far not yet been analysed in the evaluation literature though. However, since funding agencies often encourage industry-science links, having evidence on the impact of subsidized projects with specific partners would allow to shed new light on the efficacy of such policy criteria. Indeed, studies have acknowledged the role played by various partner types and the impact they may have on innovation performance (Belderbos, Carree, Diederen, Lokshin, & Veugelers, 2004; de Faria, Lima, & Santos, 2010; Faems, Van Looy, & Debackere, 2005; Kaiser, 2002). However, to date we don't know yet about their impact in light of a publicly co-financed subsidy scheme.

Before assessing the role of collaboration in an R&D subsidized context empirically, it is important to emphasize that collaboration may also be linked to certain risks. For instance, collaborating firms run the risk of free riding of one of the partners, disclosing of the firms' secrecy or weak IPR systems, rendering the appropriation of the returns of joint R&D projects difficult. Indeed, to be able to fully benefit from collaboration, a firm needs to build up specific competences and maintain a fruitful level of absorptive capacity to manage and coordinate collaborations efficiently and effectively. Otherwise, outgoing spillover effects might be higher than incoming spillover effects for some partners of the consortium, leading to the costs of collaboration being higher than the gains. Finally, incomplete contracts resulting from poor bargaining and costs of disclosure that are inherently linked to collaboration may render collaborative R&D costly if collaboration exceeds a certain threshold (Beck & Schenker–Wicki, 2014; Hottenrott & Lopes-Bento, 2014b). While such caveats are always true, they may be particularly pronounced for subsidized collaboration agreements insofar that firms may conclude collaborative R&D agreements to increase the chances of being retained for public support rather than because of true complementarity of skills or know-how between partners. Furthermore, coordination costs may be higher in the case of subsidized collaboration agreements due to monitoring or reporting duties of the funding agency.

The present analysis precisely aims at measuring such effects, by taking the type of partner within the subsidy scheme into account, thereby advising whether encouraging R&D collaboration overall, and industry-science links in particular, is an efficient policy criterion.

4 METHODOLOGICAL APPROACH AND ESTIMATION STRATEGY

4.1 Input additionality analysis

In the first step of our analysis, we are interested in estimating the treatment effect of the R&D subsidies on firms' R&D investments. As subsidies are not randomly distributed, one has to take the selection into the funding program into account in the evaluation analysis. Indeed, subsidized firms might differ from non-subsidized firms in important characteristics, and therefore the selection into the treatment has to be taken into account (Grilli & Murtinu, 2011; Heckman, LaLonde, & Smith, 1999; Imbens & Wooldridge, 2008). While several modern econometric techniques exist allowing to address such a selection bias, our study applies a non-parametric nearest neighbour propensity score matching, as this is the most adequate method for the data at hand in this study (to be presented in the next section) (Angrist, 1998; Gerfin & Lechner, 2002; Lechner, 1999; Smith & Todd, 2005).

The econometric matching allows to directly reply to the question of how much a subsidized firm would have invested in R&D if it would be in a counterfactual situation of not having received public support. Given that this counterfactual situation is never observable, it has to be estimated. Based on the assumption that we observe all the important characteristics driving the selection into the treatment (that is, provided that the conditional independence assumption (CIA) is respected (Rubin, 1977)), we can approximate this counterfactual situation by firms having the same (or very similar) characteristics than the subsidized firms, but have not received any support. In order to find such similar “twins”, we balance the subsamples of subsidized and non-subsidized firms according to the probability of receiving a subsidy. Based on a probit estimation, we obtain the conditional probability of receiving a subsidy in a single index, the propensity score. That means that we compare subsidized firms with firms that had the same probability of being subsidized, but did not receive public support. Based on this index, we apply a nearest neighbour matching estimation and use for each subsidized firm the single nearest neighbour to estimate the counterfactual situation (Dehejia & Wahba, 2002; Rosenbaum & Rubin, 1985). On top of matching on the propensity score, we further require firms of the treated and control groups to belong to the same year and the same industry.

The average treatment effect on the treated is estimated as follows:

$$\alpha_{ATT} = \frac{1}{N^T}\sum_{i=1}^{N^T}\left(R\&D_i^T - \widehat{R\&D}_i^c\right) \tag{1}$$

where $R\&D_i^T$ indicates R&D expenditures of treated firms and $\widehat{R\&D}_i^c$ the counterfactual situation, i.e. the potential outcome which would have been realized if the treatment group ($S=1$) had not been treated. $S \in \{0,1\}$ indicates the receipt of a subsidy and N^T the number of treated firms.[5]

4.2 Effectiveness of the R&D policy

In a second part, we turn to the analysis of how the additional policy-induced R&D investment translates into innovation performance. More precisely, provided that we find positive input additionality, we want to know whether the publicly induced R&D investment

[5] Finally, in order for the matching to be possible, enough common support is needed between the sample of treated firms and the sample of potential control firms. To this end, the samples of treated and control firms need to have enough overlap in terms of probability of receiving a subsidy. Observations on treated firms with probabilities larger than the maximum and smaller than the minimum of the potential control group will therefore be deleted.

is as productive as the privately invested R&D expenditures, and if such impacts differ between radical or incremental innovations.

Taking into account that not every firm in our sample has new product sales in each period, our outcome measures are characterized by a corner solution around zero (Tobin, 1958). For our analysis, we therefore use Tobit models to give point to these censored dependent variables.

In order to disentangle public from private R&D investment, we estimate the policy impact at the firm level in the same fashion as Hottenrott and Lopes-Bento (2014a) as follows:

$$\alpha_i^{TT} = R\&D_i - \widehat{R\&D^C}_i \tag{2}$$

where $\widehat{R\&D^C}_i$ is equal to R&D intensity for the counterfactual firms. Indeed, for non-subsidized firms for which α_i^{TT} is equal to zero, $\widehat{R\&D^C}_i$ corresponds to their private R&D investment. For subsidized firms, the individual treatment effect corresponds to the difference of the treated firm and its counterfactual situation, namely its unsubsidized twin. This provides the estimated treatment effect by firm, allowing to estimate the policy induced investment separately from the privately invested money on subsequent innovation performance. Furthermore, it allows to take the size of the subsidy into account.

The tobit model for $Radical_i$ can then be estimated as follows:

$$Radical^*_i = X'_{i,t-1}\beta + \epsilon_i, \epsilon_i \sim i.i.d.N(0, \sigma^2) \tag{3.1}$$

$$Radical_i = \begin{cases} Radical^*_i \; if \; X'_{i,t-1}\beta + \epsilon_i > 0 \\ 0 \; otherwise \end{cases} \tag{3.2}$$

where $Radical_i$ is the non-negative observable innovation performance variable, capturing radical innovation at the firm level. $Radical_i$ corresponds to the latent dependent variable

$Radical^{*}_{i}$ if latter is above zero and to zero otherwise. The model on the latent dependent variable, $Radical^{*}_{i}$ is estimated by a parameter vector β, and a vector of firm characteristics $X_{i,t-1}$. The latter relationship is affected by a normally distributed error, to capture randomized firm influences. The model on incremental innovation is estimated analogously.

In order for the estimates of a Tobit estimation to be consistent (see Wooldridge, 2010, pp. 680-687), homoscedasticity is required. Given that we found evidence for heteroscedasticity based on a Likelihood Ratio test, we estimate heteroscedastic robust tobit models by maximum likelihood. Therefore, we replace the homoscedastic standard error term σ with $\sigma_i = \sigma\exp(Z'\alpha)$ in the likelihood function, modeling for group-wise multiplicative heteroscedasticity by including firm size and industry dummies. Accounting for the fact that our estimates for R&D investments (α_i^{TT}, $\widehat{R\&D}^{C}$) are estimated values for the treated firms, ordinary standard errors would be biased. We thus correct our standard errors by conducting a bootstrapping procedure.[6]

5. DATA AND MODEL SPECIFICATION

5.1 Data

For the empirical analysis, the study uses a large-scale sample of Swiss firms derived from five waves (1999, 2002, 2005, 2008, and 2011) of the Swiss innovation survey, covering the years 1997-1999, 2000-2002, 2003-2005, 2006-2008 and 2009-2011. The Swiss innovation survey is a postal survey conducted by the KOF Swiss Economic Institute at the ETH Zurich, and corresponds largely to the European Community Innovation Survey following the OECD guidelines (OECD, 1992). Our data set provides us with a representative sample, covering both manufacturing and service industries. The data set contains detailed information on

[6] We bootstrap the entire procedure (inclusive of the matching) 150 times, allowing us to estimate how the sample mean of our actual sample varies due to random sampling.

firms' R&D and innovation activities, performance measures, subsidy receipts and other firm characteristics. The response rates from the surveys are: 33.8% (1999), 39.6% (2002), 38.7% (2005), 36.1% (2008), and 35.9% (2011). After eliminating missing values and limiting our sample to innovating firms only, we are left with a pooled cross-section of 6084 observations from 3552 different firms, out of which 546 received a subsidy.[7]

5.2 Dependent variables

Our analysis is separated into two main parts. For the treatment effects analysis, our outcome variable reflects the firms' R&D investment, measured as the R&D expenditures to total turnover (*RDINT*). In the second part, following Meuer, Rupietta, and Backes-Gellner (2015), our outcome variables indicate radical innovation performance (*RADICAL*), measured as the sales share of radical innovative products and incremental innovation performance (*INCREMENTAL*), measured as the sales share of significantly improved products. To define our outcome variables, we follow the definition of the Swiss Innovation Survey. I.e. radically innovative products are defined as products being radically new to the firm or to the market and incrementally innovative products are defined as products that are significantly improved compared to already existing products. Since this is the definition of both types of innovation in the survey, other studies using this data follow the same definition (see for instance Meuer et al. (2015)).[8] Studies following the same definition of radical and incremental innovation for other countries include for instance Tether and Tajar (2008) and Ritala and Hurmelinna-Laukkanen (2013).

[7] For more information on the subsidy distribution over the survey period as well as the number of sampled firms per year, see Table 1.

[8] The definition of these concepts can be explained by the size and characteristics of the Swiss market. Given that the Swiss market is rather small, closed and highly competitive, firms have to be very innovative to keep their market share. It is therefore commonly believed that a product that is new to the firm is also new to the market, as firms do not generally radically innovate for their local market only but rather for the global market. Based on this premise, the survey defines radical innovation as being new to the firm or new to the market in the Swiss Innovation Survey and incremental as being significantly improved.

5.3 Main explanatory variables

The receipt of a subsidy is indicated by a dummy (*PUBSUB*) equal to one for subsidized firms and zero otherwise. Privately invested R&D expenditures and policy-induced expenditure are denoted by $\widehat{R\&D}^C$ and α_i^{TT} respectively.

As an important part of our setting is to analyse the role of R&D collaboration, we account for various collaboration partners. A dummy variable (*RDCOOP*) simply indicates if a firm is engaged in R&D collaboration. We then distinguish between vertical (*CO_VERT*), horizontal collaboration (*CO_HOR*), and collaboration with science (*CO_SCIE*).

5.4 Other control variables

We further control for a set of variables which might influence the selection into public funding and/or drive innovation performance.

Having received a subsidy in the past might demonstrate existing competence and capabilities of the applicant and hence might influence the agency to select this firm again for a grant. We thus control for previous subsidies, where *PAST_SUBSIDY* equals one if a firm has received a subsidy in the past three years. Existing R&D capabilities may also be reflected in existing patents at the firm level. Indeed, patents may be a valid signal of previously successful R&D engagement. Consequently, we include a variable (*PAT_EMPL*) measuring patent applications per 1,000 employees to avoid potential multicollinearity with firm size. We further control for firm age (*FIRMAGE*) and (the log of) firm size (*LNFIRMSIZE*), as these are important characteristics in the funding scheme of the agency. Additionally, we take a non-linear relationship into account and control for the squared term of the two previously mentioned variables (*FIRMAGE2, LNFIRMSIZE2).* Labour productivity might also influence the agency in the approval process, as it can be seen as an indicator for high firm competitiveness. We include the natural logarithm of the sales share per employee (*LNLABPROD*). As stated by Cohen and Levinthal (1990), absorptive capacity is essential to integrate new knowledge. We therefore control for share of workforce with tertiary education in total employment (*EMPACA*). We further control for the fact that a firm belongs to a foreign group (*FOREIGN*). Subsidiaries with a foreign parent may be less likely to receive subsidies, because the parent may prefer to apply in its home country. Likewise, funding agencies may have a preference for local firms. Furthermore, foreign parents with local subsidiaries are typically larger firms and may therefore not be the priority target of the funding agency as SMEs generally constitute the main target group. It could, however, also be that firms belonging to a group may look attractive to a funding agency as the group membership possibly promises knowledge spillovers and thus economies of scope from the R&D process that go beyond national borders. It is thus unclear whether having a foreign parent plays favourably or not in receiving a subsidy from a Swiss funding agency. We take foreign market activities of a firm into account by controlling for its export activities. Highly export orientated firms might be more innovative, and hence more likely to apply for a subsidy. Export activities are measured by the export share to total turnover (*EXPORT*). In addition, we account for the level of general technological potential of a firm (*TECHPOT*) indicating the level of scientific and technological knowledge available to the firm for conducting innovation activities. *TECHPOT* is measured on a five point Likert-scale, where five indicates a high technological potential of the focal firm. Finally, five survey year dummies and seven industry sector dummies complement our set of control variables.

5.5 Timing of variables

As mentioned above, each wave of the survey covers a three-year period. In order to avoid endogeneity between the dependent variables and the covariates, we employ lagged values for the time-varying variables. Put differently, the data are measured in a way that time-varying variables are available for the three years of the survey, thereby allowing measuring the outcome at time *t* and the control at time *t-1*. In other words, while R&D investment and the share of sales of radically (or incrementally) new products are measured in period *t*, the controls are measures in period *t-1*. Table 2 provides the detail on the timing of the variables in our sample. For instance, suppose the dependent variables are measured in period *t*. Then variables such as for instance employment, export, labour productivity, patent stock per employee or higher educated employees potential are all measured in period *t-1*.

Information on variables that are assumed more stable over time, such are for instance being part of a group or collaborating in R&D activities, are available for the 3-year-period, i.e. *t-2* to *t*. For instance, "Did your firm belong to a group during the period 2009-2011?"[9] We consider age as truly exogenous and hence it is measured in period *t*.[10]

[9] See Arvanitis et al. (2013) for more information on the structure of the survey.

[10] For more information on the data structure, please refer to a review by Mairesse and Mohnen (2010), entitled "Using Innovation Surveys for econometric analysis", where the authors explain the general structure of the data in a very comprehensive way. More precisely, concerning the timing of the variables the authors explain that: "It is also the case that the innovation surveys refer to a 3-year period for most of the qualitative variables, and to the last year of that period for the quantitative variables. For instance, an enterprise may declare that they have introduced a new product on the market in the last 3 years, but its success and performance in doing so, as measured by the percentage of total sales attributed to the products introduced in the last 3 years, is assessed in the last year of that time-span." Other studies using CIS data for related analyses include for instance Arvanitis (2012); Belderbos, Carree, and Lokshin (2004); Cassiman and Veugelers (2006).

Table 2: Definition and timing of measurement of the variables.

Variable	Description
Dependent variables	
$RDINT_t$	Firms' R&D expenditures divided by total turnover in period t.
$RADICAL_t$	Sales percentage of newly introduced products in period t.
$INCREMENTAL_t$	Sales percentage of substantially improved products in t.
Independent variables	
$SUBSIDY_{t-2-t}$	Binary variable equal to 1 if a firm obtained a subsidy during the period t-2 to t, 0 otherwise.[11]
$PAST\_SUBSIDY_{t-3}$	Binary variable equal to 1 if a firm has obtained a subsidy during the previous period, i.e. t-5 to t-3 and 0 otherwise.
$FIRMAGE_t$	Age of the firm since foundation in years in period t.
$LNFIRMSIZE_{t-1}$	Natural logarithm of the number of employees (full time equivalents) in time t-1.
PAT_EMPL_{t-1}	Number of patent applications per 1,000 employees in the period t-1.
$LNLABPROD_{t-1}$	Natural logarithm of the sales share per employee in period t-1.
$FOREIGN_t$	Binary variable equal to 1 if a firm belongs to a foreign group during the period t-2 to t and 0 otherwise.
$EMPACA_{t-1}$	Share of workforce with tertiary education in total employment in t-1.
$EXPORT_{t-1}$	Share of exports in total turnover in t-1.
$RDCOOP_{t-2-t}$	Binary variable equal to 1 if a firm has engaged in R&D collaboration the period t-2 to t and 0 otherwise.
CO_VERT_{t-2-t}	Binary variable equal to 1 if a firm has engaged in R&D collaboration with vertical partners (i.e. costumers, and suppliers) in period t-2 to t and 0 otherwise.
CO_HOR_{t-2-t}	Binary variable equal to1 if a firm has engaged in R&D collaboration with horizontal partners (i.e. competitors) in t-2 to t and 0 otherwise.
CO_SCIE_{t-2-t}	Binary variable equal to 1 if a firm has engaged in R&D collaboration with science partners (i.e. universities, and other research institutes) in t-2 to t. 0 otherwise.
$TECHPOT_t$	Nominal variable measuring technological potential, i.e. scientific and technological knowledge relevant to the firm's R&D or innovation activity (on a five point Likert-scale; 1 very low, 5 very high technological potential).
$REGION_t$	Categorical variables: 1 = Lake Geneva Region; 2 = Espace Mittelland; 3 = Northwestern Switzerland; 4 = Zurich; 5 = Eastern Switzerland; 6 = Central Switzerland; 7 = Ticino.

[11] It should be noted that the fact that the subsidy receipt is measured over a 3-year-period is not a problem as firms are informed about the decision well in advance. For other studies using the treatment variable in the same manner, see for instance Aerts and Schmidt (2008); Cerulli and Potì (2012); Czarnitzki and Hussinger (2004); Czarnitzki and Licht (2006); Czarnitzki and Lopes-Bento (2014); Hottenrott and Lopes-Bento (2014a).

5.6 Descriptive statistics

Table 3 presents descriptive statistics of the variables in our analysis. Industry and size class distribution of our sample are displayed in Tables A.1 and A.2 of Appendix 1. As presented in Table 3, significant differences in the means of almost all variables between the subsidized firms and the non-subsidized firms exist. For instance, on average, subsidized firms are more likely to have experience in the past with subsidies, are slightly larger, have more approved patents per employee, have a higher likelihood belonging to a foreign group, have a higher educated workforce, are more export-oriented, have a higher technological potential, and engage more in R&D collaboration. Notably, they do not differ in firm age and labour productivity. With respect to the outcome variable, in alignment with our expectation, subsidized firms have on average higher R&D investments. However, at this point, we do not know how much of these additional R&D expenditures are induced by the subsidy or are due to other firm characteristics.

Table 3: Descriptive statistics on innovating firms.

	Unsubsidized firms, N = 5,538		*Subsidized firms, N = 546*		*Results of t-tests on mean differences*
Variables	Mean	Std.dev.	Mean	Std.dev.	
			Covariates		
PAST_SUBSIDY	0.016	0.124	0.203	0.403	***
FIRMAGE	65.2	42.2	68.2	54.0	
FIRMAGE2	6034.9	10583.9	7562.7	21140.4	*
LNFIRMSIZE	4.269	1.410	4.930	1.515	***
LNFIRMSIZE2	20.215	13.411	26.597	16.368	***
PAT_EMPL	12.904	143.565	31.965	90.542	***
LNLABPROD	12.509	0.752	12.505	0.650	
FOREIGN	0.158	0.365	0.200	0.400	**
EMPACA	5.760	11.413	11.875	16.974	***
EXPORT	25.498	34.307	51.031	38.591	***
RDCOOP	0.186	0.389	0.639	0.481	***
CO_VERT	0.174	0.379	0.560	0.497	***
CO_HOR	0.066	0.248	0.220	0.414	***
CO_SCIE	0.094	0.291	0.570	0.496	***
TECHPOT	2.788	1.144	3.484	0.977	***
			Outcome variable		
RDINT	1.400	3.894	5.747	13.606	***

6. EMPIRICAL ANALYSIS AND DISCUSSION

6.1 Average effect of public funding on subsidized firms

As described above, we employ a matching estimation to identify the average treatment effect of public R&D grants on the treated firms. To be able to apply the matching estimator, we need to predict the probability of receiving public R&D funding. Therefore, we estimate a probit model on a subsidy receipt incorporating important characteristics for the selection into the funding scheme. As can be seen in Table 4, with the exception of firm age, patents per employee, and being member of a foreign group, all our covariates are important drivers for the selection into the treatment.[12]

Table 4: Probit estimation on the probability of receiving a subsidy.

Variables	Coefficient	Standard errors
PAST_SUBSIDY	1.149***	(0.100)
FIRMAGE	-0.001	(0.000)
FIRMAGE2	0.000	(0.000)
LNFIRMSIZE	0.142*	(0.090)
LNFIRMSIZE2	-0.004	(0.010)
PAT_EMPL	0.000	(0.000)
LNLABPROD	-0.217***	(0.040)
FOREIGN	-0.082	(0.070)
EMPACA	0.013***	(0.000)
EXPORT	0.004***	(0.000)
RDCOOP	0.770***	(0.060)
TECHPOT	0.148***	(0.030)
No. of observations	6084	
Log likelihood	-1392.4211	
Joint significance of industry dummies	$\chi 2(6) = 19.92$***	
Joint significance of survey year dummies	$\chi 2(4) = 27.01$***	

Note: The model includes a constant, industry and survey year dummies (not presented). *** (**, *) indicate a significance level of 1% (5%, 10%).

Table 5 presents the results of our econometric matching estimation. We can see that all our covariates are well-balanced after the matching. This points to the fact that our matching was successful and that we found a close neighbour for each of our treated firms. The only variable that remains statistically significant is the outcome variable. We can thus attribute this difference to the treatment and can conclude that, in line with the literature, full crowding out can be rejected.

In order to take a potential selection on unobservables into account, we test the robustness of our matching estimation by conducting an IV regression. The results of the IV regression as

[12] It should be noted that due to the potential endogeneity of R&D collaboration, we have estimated an IV regression on R&D subsidies, instrumenting R&D collaboration. This did not change our findings as R&D collaboration remained highly significant in the second stage (and the instruments pass all the statistical tests in the first stage). The detailed regression results can be obtained by the authors upon request.

well as the choice of our IVs are presented in detail Appendix 2 (Table A.3). Conclusions remain unchanged even if we allow for a selection on unobservables.

Table 5: Average treatment effect of public R&D funding.

	Selected control group, N=530		*Subsidized firms, N=530*		*p-value of t-tests on mean differences*
Variables	Mean	Std.dev.	Mean	Std.dev.	
			Covariates		
PAST_SUBSIDY	0.145	0.353	0.179	0.384	0.195
FIRMAGE	69.8	47.2	68.4	54.1	0.707
FIRMAGE2	7097.0	11617.0	7605.1	21382.6	0.656
LNFIRMSIZE	4.765	1.452	4.891	1.485	0.234
LNFIRMSIZE2	24.815	14.577	26.120	15.855	0.228
PAT_EMPL	20.623	54.565	28.963	79.044	0.072
LNLABPROD	12.483	0.668	12.496	0.648	0.784
FOREIGN	0.183	0.387	0.198	0.399	0.591
EMPACA	12.578	19.054	11.259	16.303	0.311
EXPORT	49.026	38.315	50.302	38.537	0.644
RDCOOP	0.632	0.483	0.628	0.484	0.913
TECHPOT	3.453	1.015	3.457	0.974	0.958
			Outcome variable		
RDINT	3.453	5.859	5.698	13.717	0.001

Note: *** (**, *) indicate a significance level of 1% (5%, 10%). 16 observations are lost because of the common support condition.

6.2 The impact on innovation performance

In the following section, we turn to the analysis on innovation performance, as measured by the sales share of radically and incrementally new products respectively. Before turning to the analysis, we provide some additional descriptive information on the variables that have not been used so far.

More precisely, in Table 6 we show the distribution of radical and incremental innovation sales, as well as the distribution of policy induced and privately motivated R&D investment. We can see that the average sales share from radically new products is of 14.4% in our sample. Incremental innovations account for 16.7% of the total turnover of the firms in our sample. The average treatment effect amounts to 0.13%, while the private R&D investments corresponds to 1.86%. Furthermore, we see that even though the average treatment effect is positive, we have also some firms that experience a negative additionality. Specifically, as shown by Table 7, 43% of the treated firms have a negative alpha. In other words, for 43% of the firms, the R&D expenditures did not go up, but to the contrary, the firms spent less money on R&D even though they have received a subsidy. This can happen in case a project gets abandoned for instance, and all the related expenditures get cancelled as a consequence. While this may seem high, very similar results have been found for subsidized firms in Belgium, where 43,5% of subsidized firms experienced a negative additionality (see Hottenrott et al., 2014). Roughly 9% of the subsidized firms have an additionality of zero, meaning that they have spent exactly what they have received from the government, thereby not creating additional R&D expenditures in the economy. Finally, the lion's share of the subsidized firms (46.5%) has a positive additionality, as one would expect by the way the policy is constructed. In different words, these firms have respected to co-financing clause and have added private money to increase their overall R&D expenditures. Finally, 0.1% have an additionality above 50, which means that they invest over half of their turnover in R&D. While this may seem unlikely, it should be noted that it concerns only 5 firms, two of which are very small (6 employees and 9 employees respectively). For such small firms, very high additionalities are not surprising.

Table 6: Additional descriptive statistics, N= 4,862.

Variables	Observations	Mean	Std.dev.	Min.	Max.
RADICAL	4,862	14.406	18.139	0	100
INCREMENTAL	4,862	16.706	19.654	0	100
α_i^{TT}	4,862	0.127	3.899	-52.134	100.0
$\widehat{R\&D}^C$	4,862	1.862	4.218	0	55.6

Table 7: Descriptive statistics on the output additionalities α_i^{TT}, accounting for firm size and age, N=477.[13]

Percentages of firms		Firm Size			Firm Age			
N=477		S = 1–49	M = 50 – 249	L = 250-max.	<15	16-30	31-75	76-max.
$\alpha_i^{TT} < 0$	43.40	15.94	51.69	32.37	6.28	10.63	41.55	41.55
$\alpha_i^{TT} = 0$	9.01	23.26	34.88	41.86	9.30	23.26	27.91	39.53
$\alpha_i^{TT} > 0$	46.54	29.52	43.17	27.31	4.85	22.91	39.65	32.60
$\alpha_i^{TT} > 50$	1.05	40.00	-	60.00	-	20.00	60.00	20.00

Table 8 displays the results of the heteroscedasticity-robust Tobit models on innovation outcome. Models one to five relate to the impact of both types of R&D investment on radical innovation, while models six to ten relate to incremental innovation. The various models per category take into account different collaboration patterns.

Our baseline model for the impact on radical innovation (Model I), shows that both, policy-induced as well as privately invested R&D are positive and highly significant. Furthermore, we see that the coefficients are of a similar size. Put differently, a 10% increase in the counterfactual R&D investment would lead to a 4,4 percentage point increase in the estimated latent dependent variable, i.e. the estimated sales share in radical innovation sales, on average, while a 10% increase in policy induced R&D investment would lead to a 3,7

[13] It should be noted that the number of subsidized firms corresponds to the number of subsidized firms of the Tobit models, where we lose some observations because of missing values in the outcome variables.

percentage point increase in the estimated latent variable. Models two and three, containing a dummy for overall collaboration (Model II) and three dummies for vertical, horizontal and collaboration with science (Model III) respectively, show that neither overall, nor a specific type of collaboration displays a significant effect on the estimated sales share in radical innovation. Policy-induced as well as privately motivated R&D investments stay positive and of the same magnitude.

Next, to assess whether these effects change in light of the receipt of a subsidy, we interact privately as well as publicly induced R&D investment with different collaboration patterns. Model IV starts by interacting the overall collaboration dummy with both types of R&D investment. We see that neither one of the interaction terms is significant. In other words, the R&D investments driven by collaboration do not impact the estimated sales share of radical innovation. The same conclusion can be drawn for Model V, where we interact the three different types of collaboration with both types of R&D investment. We can thus conclude that collaborating, with science or another partner, does not improve the policy impact of the subsidy in terms of radical innovation sales.

Turning to the impact on incremental innovation, we see that in line with our expectations, privately motivated R&D expenditures are significant. What strives our attention is the non-significant result of the publicly induced R&D investment, α_i^{TT} (Model VI). While the coefficient is larger in magnitude than it is for radical innovation, it is not statistically significant. Even though the funding agency also supports incremental innovation projects, this finding points to the fact that the publicly induced part of the R&D investment mainly impacts radical innovation.

Going forward, we control for overall collaboration (Model VII) before differentiating between the types of external collaboration partners, namely horizontal, vertical and diagonal collaboration (Model VIII). As was the case for the radical innovation sales share, neither one of the collaboration dummies is significant, nor do they impact the results from the baseline model. When interacting both types of R&D investment with the collaboration dummy, we see that while the counterfactual R&D spending stays significant and positive, both privately and publicly invested parts of the investment that are interacted with collaboration are insignificant.

Finally, in Model X we interact both types of R&D investment with the three different collaboration types. While collaboration with science overall displays a positive and significant impact in this case (as well as the counterfactual R&D spending), we see that parts of these positive impacts turn negative when driven by collaboration (CO_SCIE*$\widehat{R\&D}^{C}$). Furthermore, when publicly induced R&D investment is driven by horizontal collaboration, the insignificant impacts of these variables turns negative and significant if interacted (CO_HOR*α_i^{TT}).

While the results of our models containing collaboration information may seem surprising, there may be several reasons able to explain such findings. For radical innovation, neither one of the collaboration installations have any impact on sales success, even though the funding agency encourages R&D collaboration between firms and especially between firms and science. One explanation for the insignificant results may be the fact that Switzerland is a relatively closed country, where firms are not used to collaborate (as a matter of illustration, roughly 13% of the firms in Switzerland collaborate, compared to some 30% in Belgium for instance). Hence, firms may have developed the necessary skills and know-how over the years and are therefore less dependent on pooling resources with external partners. In this case, collaboration costs may indeed exceed gains in certain settings. In the case of Model X the fact that collaboration with science is negative may be explained by the fact that typically, collaboration with science is needed when firms intend undertaking path-breaking innovations, pushing the technological frontier. For incremental innovation, such type of collaboration is therefore not necessarily attractive, and may deviate resources from where they could have been invested more appropriately in terms of incremental change to existing products. Hence, if the strategy of the firm is to ensure long-term survival perspectives through incremental innovation, it seems that collaborating with science is not maximizing its partnership behaviour. The negative impact of collaboration with competitors (horizontal collaboration) and its impact on the sales share of incremental innovation can be explained by the fact that incremental innovations are often times easier to imitate than radical innovations. Teaming up with a competitor may therefore mean losing parts of the market to that partner.

In terms of policy effects in light of collaboration type, our results thus do not show any evidence that subsidized collaborating firms are more productive in terms of new products than non-subsidized firms. To the contrary, we even find weak, yet negative results for the interaction of policy driven investment and horizontal and science collaboration. While the overall policy effect of the Swiss funding agency is positive, the encouragement of collaboration should be revisited.

Before concluding, it should be noted that we took the potential endogeneity of our collaboration variables into account. In Appendix 3, we estimate a structural equation as introduced by Smith and Blundell (1986) to see if our results are driven by endogenetiy. As shown by the results in Table A.4, our findings are not driven by endogeneity. Furthermore, we allowed for a longer time lag as one may argue that the impact of both types of R&D investment or collaboration may need more time to impact radical than incremental innovations. As can be seen by Table A.5 in Appendix 4, our conclusions remain unchanged if we allow for a longer time lag. Finally, we also re-estimated the main models controlling for other innovation expenditures. Indeed, one may argue that the way R&D translates into marketable products also depends on the expenditures done on top of R&D investment, independent of whether R&D was subsidized or not.[14] We therefore control for innovation expenditures in the regressions of Table A.6 in Appendix 5, to see if our findings hold for a given level of innovation investment.[15] As can be seen from Table A.6, our conclusions remain unchanged.

It should be noted that due to the lower number of observations in the estimations with an additional time lag and in the estimations including other innovation investment, the significance levels drop slightly, as the lower number of observations induces larger standard errors.[16]

[14] We thank an anonymous referee for pointing this out.

[15] Innovation expenditures include R&D expenditures, but also other expenditures needed in the innovation process, such as expenditures for construction and design, further follow-up investments, including acquisition of other external knowledge, acquisition of specific machinery or software needed for the development or finalization of technologies, as well as expenditures related to the certification of products or packaging technology. Innovation investment enters the equation net of R&D expenditures to avoid double counting.

[16] The missing observations in the models with additional time lags are due to the unbalanced nature of our panel. The missing values in the estimation containing net innovation investment is due the missing values in this variable.

Table 8: Heteroscedasticity-robust Tobit estimates on radical and incremental innovation performance.

	RADICAL					*INCREMENTAL*				
Variables	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX	Model X
α_i^{TT}	0.371**	0.370**	0.366**	0.203	0.237	0.522	0.521	0.526	0.214	0.289
	(0.153)	(0.154)	(0.153)	(0.377)	(0.356)	(0.349)	(0.352)	(0.361)	(0.395)	(0.383)
$\widehat{R\&D}^C$	0.444***	0.437***	0.428***	0.512***	0.548***	0.364**	0.352**	0.332**	0.782***	0.770***
	(0.119)	(0.117)	(0.121)	(0.158)	(0.158)	(0.148)	(0.144)	(0.146)	(0.235)	(0.207)
RDCOOP		0.416		0.540			0.735		2.126**	
		(0.909)		(0.927)			(1.029)		(0.979)	
FIRMAGE	-0.064***	-0.064***	-0.064***	-0.064***	-0.063***	-0.120**	-0.121***	-0.121***	-0.120***	-0.118***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.047)	(0.047)	(0.047)	(0.046)	(0.045)
FIRMAGE2	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LNFIRMSIZE	0.889	0.884	0.934	0.936	1.018	-0.924	-0.930	-0.739	-0.940	-0.627
	(0.917)	(0.919)	(0.916)	(0.945)	(0.969)	(1.172)	(1.171)	(1.147)	(1.170)	(1.121)
LNFIRMSIZE2	-0.095	-0.096	-0.104	-0.101	-0.111	0.117	0.114	0.087	0.116	0.081
	(0.091)	(0.091)	(0.092)	(0.094)	(0.098)	(0.115)	(0.115)	(0.111)	(0.115)	(0.108)
EXPORT	0.053***	0.053***	0.052***	0.052***	0.052***	0.043***	0.042***	0.044***	0.040***	0.043***
	(0.015)	(0.016)	(0.014)	(0.015)	(0.014)	(0.014)	(0.013)	(0.012)	(0.014)	(0.012)
TECHPOT	1.399***	1.373***	1.336***	1.356***	1.276**	2.151***	2.109***	2.006***	2.021***	1.838***
	(0.436)	(0.422)	(0.456)	(0.434)	(0.501)	(0.389)	(0.381)	(0.390)	(0.394)	(0.429)

continued

continued	*RADICAL*					*INCREMENTAL*				
	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX	Model X
CO_VERT			-0.542		-1.534			0.329		-1.172
			(1.763)		(1.874)			(1.157)		(1.341)
CO_HOR			0.227		0.074			3.334		4.707
			(1.480)		(2.231)			(3.220)		(3.903)
CO_SCIE			1.392		3.115			0.257		3.396*
			(2.078)		(2.926)			(2.276)		(1.900)
RDCOOP*α_i^{TT}				0.386					0.663	
				(0.673)					(0.638)	
RDCOOP *$\widehat{R\&D}^C$				-0.101					-0.678	
				(0.215)					(0.416)	
CO_VERT*α_i^{TT}					0.322					0.683
					(0.670)					(0.800)
CO_VERT*$\widehat{R\&D}^C$					0.383					0.431
					(0.276)					(0.267)
CO_HOR*α_i^{TT}					0.381					-0.847*
					(0.489)					(0.507)
CO_HOR*$\widehat{R\&D}^C$					0.077					-0.362
					(0.424)					(0.312)
CO_SCIE*α_i^{TT}					-0.073					0.135
					(0.607)					(0.740)
CO_SCIE*$\widehat{R\&D}^C$					-0.644					-1.103***
					(0.434)					(0.406)
No. of observations	4,862	4,862	4,862	4,862	4,862	4,862	4,862	4,862	4,862	4,862

Source: Own calculations. Data derived from the Innovation survey conducted by the Swiss Economic Institute (KOF). Note: Standard deviations in parentheses are clustered at the firm level and bootstrapped with 150 replications. Time and industry dummies are jointly significant (not presented). *** (**, *) indicate a significance level of 1% (5%, 10%).

7. CONCLUSION

Our study is an extension of previous studies interested in the effects of public R&D polices on input and/or output additionality. We contribute to current knowledge on the effect of such policy by providing evidence as to where the policy impact is highest, radical or incremental innovation. Furthermore, we take specific collaboration patterns into account to see whether these impacts are affected by R&D collaboration as well as the type thereof (i.e. horizontal, vertical or with science).

In terms of input additionality, we find, in line with previous studies, evidence that allows rejecting the null hypothesis of full crowding out. Taking into account the degree of novelty in terms of innovation performance, this analysis fills a gap by providing evidence on the fact that the impact of the Swiss funding agency is higher for radical than for incremental innovation, as there is no significant impact for the latter in terms of policy induced R&D expenditures. In line with our expectations, privately invested R&D expenditures are positive and significant for both types of innovation output.

Given that the Swiss funding policy encourages firms to collaborate in their R&D activities, our work integrates information on firms' collaboration status. Compared to previous studies that only consider whether or not a firm qualifies as collaborator, we additionally account for specific types of collaboration partners. We are thus able to investigate the effects of different collaboration constellations, i.e. horizontal, vertical and collaboration with science in our framework. While the fact of collaborating as such does not impact the sales share of either incremental or radical innovation, we find that when collaboration types are interacted with R&D investment, parts of the investment driven by collaboration (horizontal and science) turns negative in the case of incremental innovation. Hence, the policy effect is not enhanced by a specific collaboration strategy and collaborative R&D should not necessarily constitute a priority for the Swiss funding agency.

Combing strategic management literature on radical vs. incremental innovation and on collaboration impacts with literature on policy evaluation, our study also allows drawing implications from a managerial perspective. From a managerial point of view, the findings are relevant from mainly two angles. In terms of subsidy strategy, it is vital for a manager to know that it is more likely for a subsidy to have the desired impact when used for more radical innovation projects. From a collaboration strategy perspective, it is important to know that there are also downsides to engaging into collaboration. Hence, if tempted to engage in R&D collaborations in order to increase the probability of receiving a subsidy, managers should be aware that there may also be downsides to this strategy, and that the impact of the subsidy may even turn negative in light of collaboration.

Despite all efforts, our analysis is not without limitation. One improvement would be to have access to panel data, allowing to follow firms over time, thereby being able to analyse the impact of a subsidy in a before-after setting. Furthermore, having information about the rejected applicants would have allowed for a series of additional robustness checks to strengthen our findings.

Appendices

Appendix 1: Additional descriptive statistics

Table A.1: Industry distribution.

Industry	Number of firms	Percentages	Percentage of subsidized firms per sector
1 Construction, mining, energy	441	7.25	5.90
2 Consumer goods (food, beverages, tobacco, textiles, clothing)	433	7.12	9.01
3 Intermediate goods (paper, printing, chemicals, pharmaceuticals, rubber, plastics, minerals, basic metals)	1,051	17.27	9.13
4 Investment goods (fabricated metals, machinery & equipment, electrical equipment, electronics and optical products, medical instruments, watches, vehicles, and other manufacturing)	2,111	34.7	13.55
5 Traditional services (trade, transportation, telecommunications)	923	15.17	4.55
6 Knowledge-based services (banking, insurance, information technology & services, technical commercial services)	874	14.37	5.72
7 Other services	251	4.13	2.79
Total	**6,084**	**100**	**8.97 (on average)**

Table A.2: Size class distribution.

Size class	Size class distribution	Number of firms	Percentages	Percentage of subsidized firms per size class
1 Small-sized firms	1 – 49	2,489	40.91	5.10
2 Medium-sized	50 – 249	2,405	39.53	10.27
3 Large-sized	250 – max.	1,190	19.56	14.45
	Total	**6,084**	**100**	**8.97 (on average)**

Appendix 2

Robustness check for the matching estimation accounting for potential selection on unobservables

An essential assumption to conduct a valid matching estimation is the conditional independence assumption (CIA). Indeed, for the matching estimation to be valid, the outcome has to be statistically independent of program participation, conditional on a series of observable characteristics. This fundamental assumption is however not testable. Therefore, we test the robustness of our matching estimation results by taking into account the selection on observables. We do so using an instrumental variables (IV) approach.

To conduct our IV regression, we employ two instruments for the subsidy receipt. First, we use the likelihood of receiving a subsidy by region and industry (IV_1); and second, we use the likelihood of collaborating with science by industry (IV_2).

IV_1 is justified by the fact that funding agencies often have preferences in terms of location or industries. Even though such priorities are not formal conditions, it may very well be that a firm based in direct proximity of a funding agency is more aware of the policy and is more visible to the decision makers than a firm that is situated further away. Hence, being part of a region or an industry where the likelihood of receiving a subsidy is high, is likely to impact the receipt of a subsidy of firm *i*. The rationale of using the industry average of collaboration with science institutions as an instrument (IV_2) documents the fact that some technological trajectories have closer relationships to universities and other research centres. Having a closer relationship to science collaboration increases the likelihood of being retained for funding, given that the Swiss government aims at increasing industry – science links.

Both instruments fulfil the statistical tests for being valid instruments. In the first stage, both IVs are highly significant. In the second stage, the Hansen J-test of overidentification is insignificant. Hence, both from a statistical as well as from an economic point of view, our instruments are valid. As displayed in Table A.4, the results of the IV estimation are in line with what we find in our matching estimation.

Table A.3: Robustness test with instrumental variables for subsidies on R&D intensity.

Variables	*First stage* SUBSIDY	*Second stage* *2SLS on R&DINT*
SUBSIDY_REG_IND (IV_1)	0.672***	
	(0.058)	
CO_SCIE_IND (IV_2)	0.404***	
	(0.118)	
SUBSIDY		6.363***
		(1.804)
PAST_SUBSIDY	0.330***	0.424
	(0.034)	(1.719)
FIRMAGE	0.000	-0.005*
	(0.000)	(0.003)
FIRMAGE2	0.000	0.000
	(0.000)	(0.000)
LNFIRMSIZE	0.003	-0.713**
	(0.012)	(0.342)
LNFIRMSIZE2	0.001	0.049
	(0.001)	(0.032)
PATCOUNT_E~L	0.000	0.005***
	(0.000)	(0.002)
LNLABPROD	-0.012***	-0.636***
	(0.004)	(0.157)
FOREIGN	-0.020*	0.515
	(0.011)	(0.331)
EMPACA	0.002***	0.083***
	(0.000)	(0.020)
EXPORT	0.000***	0.019***
	(0.000)	(0.005)
RDCOOP	0.135***	0.030
	(0.011)	(0.372)
TECHPOT	0.012***	0.235***
	(0.003)	(0.059)
No. of observations	6,084	6,084
Uncentered R2	0.291	0.232
F-Test of excl. instruments	F(2, 3551) = 71.52***	
Hansen's J test statistic		$\chi2(1)$)= 0.971

Note: IV_1 is the region and industry mean of the likelihood of receiving a subsidy. IV_2 is the industry sector mean of the likelihood of collaborating with science institutes. Both models include an intercept, time and industry dummies (not presented). Standard errors (in parentheses) are clustered at the firm level. *** (**, *) indicate a significance level of 1% (5%, 10%).

Appendix 3

Robustness check for potential endogeneity of the collaboration variable in the innovation outcome equation

In our innovation outcome estimations, we face the problem that one of our main explanatory variable might be endogenous, namely our collaboration variables. In order to test if our results are affected by potential endogeneity, we conduct a structural equation approach introduced by Smith and Blundell (1986). For the sake of this robustness check, we defined two instrumental variables for our potential endogenous collaboration variable *RDCOOP* following the advices of Murray (2006). Our first instrumental variable *IND_COOP* (IV_1) captures the share of collaborating firms by industry (at nace-2-level) in previous years. The rationale behind this instrument is that the higher the share of collaborating firms in a given industry, the higher is the probability that a firm i in industry j engages in collaboration in a given period. Our second instrumental variable *COOP_EXP* (IV_2) is defined as the overall collaboration experience of a firm i in our sample, and takes values from 0 to 5. The more experience a firm has in collaboration, the higher the likelihood of this firm to engage in a collaboration again.

To further test the statistical validity of our instruments employed for the Blundell-Smith test of exogeneity, we ran a couple of tests on the validity of the chosen instruments. It should be noted though that we have to use the standard Two Stage Least Squares (2SLS) approach, as standard tests of over-identification do not exist for the Blundell-Smith approach. Our two excluded instruments are jointly statistical significant at the 1%-level ($F(2, 2722) = 647.97$), and the Hansen J test of over-identification cannot be rejected for radical innovation performance (Hansen J statistic = 2.540, $p=.111$), nor for incremental innovation performance (Hansen J statistic = 2.578, $p=.108$). Finally, both our instruments are statistically significant in the first stage of the equation. Considering the above results, we can conclude that our two instrumental variables satisfy the statistical requirements.

As can be see seen in Table A.4, the first stage residuals are not significant in the innovation outcome equations. Therefore, we can conclude that our findings are not driven by endogeneity.

Table A.4: Robustness test with instrumental variables for R&D collaboration on innovation outcomes.

Variables	First stage Probit: RDCOOP	Second stage Tobit: RADICAL	INCREMENTAL
IND_COOP (IV_1)	-0.560*		
	(0.307)		
COOP_EXP (IV_2)	1.146***		
	(0.047)		
RDINT	0.011	0.446***	0.387***
	(0.007)	(0.068)	(0.081)
FIRMAGE	-0.001	-0.061***	-0.080***
	(0.001)	(0.014)	(0.017)
FIRMAGE2	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
LNFIRMSIZE	0.01	0.865	-1.235
	(0.072)	(1.083)	(1.269)
LNFIRMSIZE2	-0.003	-0.08	0.124
	(0.007)	(0.109)	(0.129)
EXPORT	0.001	0.031***	0.043***
	(0.001)	(0.011)	(0.012)
TECHPOT	0.096***	1.652***	2.278***
	(0.027)	(0.310)	(0.361)
RDCOOP		1.283	0.12
		(1.210)	(1.398)
1^{ST} STAGE RESIDUALS		-0.026	0.248
		(0.172)	(0.198)
No. of observations	4,224	4,224	4,224

Note: IV_1 represents the industry mean of collaborating firms in previous years. IV_2 reflects the firm's overall collaboration experience. The second stage Tobit models employ heteroscedastic-robust estimations. All stages include an intercept, time and industry dummies (not presented). Standard errors (in parentheses) are clustered at the firm level. *** (**, *) indicate a significance level of 1% (5%, 10%).

Appendix 4: Using a different time structure

Table A.5: Robustness check controlling for additional time lags (including a survey-time-lag, corresponding to a 4-year-time-lag). Heteroscedasticity-robust Tobit estimates on radical and incremental innovation performance.

	RADICAL					*INCREMENTAL*				
Lagged variables	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX	Model X
α_i^{TT}	0.809*	0.802*	0.808*	0.837	0.844	0.114	0.106	0.113	0.031	0.034
	(0.441)	(0.451)	(0.449)	(0.631)	(0.570)	(0.466)	(0.460)	(0.464)	(0.837)	(0.743)
$\widehat{R\&D}^C$	0.844***	0.811***	0.835***	0.809***	0.813***	0.875***	0.859***	0.863***	0.874***	0.873***
	(0.165)	(0.164)	(0.169)	(0.279)	(0.307)	(0.215)	(0.227)	(0.222)	(0.318)	(0.311)
RDCOOP		4.238***		4.411***			1.800		1.664	
		(1.399)		(1.214)			(1.899)		(2.397)	
FIRMAGE	-0.017	-0.017	-0.017	-0.018	-0.018	-0.026	-0.027	-0.025	-0.026	-0.025
	(0.039)	(0.040)	(0.039)	(0.040)	(0.039)	(0.034)	(0.035)	(0.035)	(0.035)	(0.035)
FIRMAGE2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LNFIRMSIZE	4.045**	4.214**	4.408***	4.110**	4.165***	-0.259	-0.172	-0.125	-0.005	0.036
	(1.787)	(1.725)	(1.693)	(1.674)	(1.618)	(2.292)	(2.268)	(2.307)	(2.254)	(2.244)
LNFIRMSIZE2	-0.155	-0.193	-0.214	-0.185	-0.192	0.249	0.233	0.224	0.219	0.213
	(0.200)	(0.187)	(0.180)	(0.179)	(0.168)	(0.243)	(0.242)	(0.243)	(0.240)	(0.235)
EXPORT	0.042**	0.033	0.038*	0.034	0.038*	0.079***	0.075***	0.077***	0.074***	0.075***
	(0.021)	(0.022)	(0.022)	(0.021)	(0.020)	(0.024)	(0.022)	(0.023)	(0.022)	(0.023)
TECHPOT	1.437***	1.255**	1.214**	1.250**	1.205**	1.922***	1.856***	1.835***	1.858***	1.810***
	(0.492)	(0.496)	(0.490)	(0.499)	(0.508)	(0.553)	(0.538)	(0.539)	(0.538)	(0.536)

continued

continued	*RADICAL*					*INCREMENTAL*				
	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX	Model X
CO_VERT			2.193		0.752			2.451		1.947
			(1.628)		(1.955)			(2.788)		(3.730)
CO_HOR			5.955**		5.449			2.208		1.543
			(2.961)		(3.967)			(2.220)		(2.785)
CO_SCIE			-0.666		1.313			-1.448		-0.851
			(2.032)		(3.006)			(2.389)		(2.914)
RDCOOP*α_i^{TT}				-0.242					0.420	
				(0.671)					(0.865)	
RDCOOP *$\widehat{R\&D}^C$				-0.033					0.004	
				(0.436)					(0.459)	
CO_VERT*α_i^{TT}					0.410					0.381
					(1.094)					(1.217)
CO_VERT*$\widehat{R\&D}^C$					0.556					0.271
					(0.445)					(0.670)
CO_HOR*α_i^{TT}					0.575					-0.249
					(0.753)					(1.010)
CO_HOR*$\widehat{R\&D}^C$					0.173					0.262
					(0.515)					(0.539)
CO_SCIE*α_i^{TT}					-0.780					0.312
					(1.097)					(1.347)
CO_SCIE*$\widehat{R\&D}^C$					-0.643					-0.326
					(0.704)					(0.594)
No. of observations	1,924	1,924	1,924	1,924	1,924	1,924	1,924	1,924	1,924	1,924

Note: Standard deviations in parentheses are clustered at the firm level and bootstrapped with 150 replications. Time and industry dummies are jointly significant (not presented). *** (**, *) indicate a significance level of 1% (5%, 10%).

Appendix 5: Accounting for other innovation investments

Table A.6: Robustness check: Heteroscedastic-robust Tobit estimates on radical and incremental innovation performance, holding other innovation investments constant.

	RADICAL			*INCREMENTAL*		
Variables	Model I	Model II	Model III	Model VI	Model VII	Model VIII
α_i^{TT}	0.416*	0.417*	0.418*	0.598	0.599	0.603
	(0.250)	(0.254)	(0.251)	(0.381)	(0.386)	(0.397)
$\widehat{R\&D}^{C}$	0.528***	0.518***	0.539***	0.749***	0.715***	0.689***
	(0.147)	(0.152)	(0.155)	(0.244)	(0.235)	(0.232)
INNO_INV	0.303***	0.303***	0.301***	-0.282	-0.281	-0.283
	(0.091)	(0.091)	(0.092)	(0.257)	(0.255)	(0.257)
RDCOOP		0.464			1.750*	
		(1.206)			(1.054)	
CO_VERT			2.136*			-0.085
			(1.267)			(1.618)
CO_HOR			-2.046			2.384
			(2.824)			(2.247)
CO_SCIE			-1.994			2.669
			(1.623)			(1.647)
FIRMAGE	-0.127**	-0.127**	-0.129**	-0.097***	-0.098***	-0.095***
	(0.054)	(0.055)	(0.056)	(0.031)	(0.032)	(0.031)
FIRMAGE2	0.000*	0.000*	0.000*	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LNFIRMSIZE	1.446	1.438	1.352	3.604	3.592	3.657
	(1.198)	(1.189)	(1.169)	(2.318)	(2.287)	(2.257)
LNFIRMSIZE2	-0.122	-0.123	-0.110	-0.310	-0.314	-0.329
	(0.115)	(0.113)	(0.111)	(0.217)	(0.214)	(0.211)
EXPORT	0.054**	0.053**	0.053**	0.019	0.016	0.015
	(0.023)	(0.024)	(0.023)	(0.019)	(0.020)	(0.019)
TECHPOT	1.257**	1.235**	1.320***	2.255***	2.172***	2.060***
	(0.527)	(0.498)	(0.462)	(0.459)	(0.454)	(0.443)
No. of observations	3,477	3,477	3,477	3,477	3,477	3,477

Note: Bootstrapped standard deviations in parentheses are clustered at the firm level. Time and industry dummies are jointly significant (not presented). *** (**, *) indicate a significance level of 1% (5%, 10%).

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